UAV Control in Smart City Based on Space-Air-Ground Integrated Network

TAN Shihan
School of Command and Control Engineering College,
Army Engineering University of PLA
Nanjing, China
E-mail: 765858495@qq.com

DUN Congying
School of Command and Control Engineering College,
Army Engineering University of PLA
Nanjing, China

JIN Fenglin *
School of Command and Control Engineering College,
Army Engineering University of PLA
Nanjing, China
E-mail: 1834427389@qq.com

XU Kun
School of Command and Control Engineering College,
Army Engineering University of PLA
Nanjing, China

***Abstract*—Unmanned Aerial Vehicle (UAV) is an important part of the wireless network system of the future smart city. As a difficult point in the large-scale application of UAV, UAV control gradually attracts people's attention. Aiming at the problems of UAV control in smart city application, a near real time online learning architecture of UAV control based on the software-defined space-air-ground integrated network (SSAG) was proposed. This architecture uses the two-layer software defined network (SDN) controller architecture of SSAG framework to separate UAV control. The upper-tier SDN controller is responsible for the scheduling of UAV configuration, while the lower-tier SDN controller is responsible for regional coordination of UAV. The upper-tier SDN controller updates the tendency of network states by acquiring network states information in time interval. By simulating the network state in the next time interval, the optimal strategy of UAV scheduling of the next time interval is obtained by using the strategy iteration algorithm. Finally, an example is given to verify that the near real-time online learning architecture can accurately predict the UAV requirement, and increase the throughput of the network system compared with the traditional approach.**

Keywords-UAV;Software Defined Space-Air-Ground Integrated Network (SSAG); Software Defined Network (SDN); UAV control; smart city; Space-Air-Ground Integrate Network (SAGIN)

I. INTRODUCTION

As an efficient urban framework, smart city is the main trend of urban development in the future [1]. However, thousands of intelligent devices in smart city will generate great pressure to wireless network transmission [2].

It is not cost-effective to add more ground network resources to meet the traffic demand. On the one hand, with high spatial-temporal dynamics of network flow, network congestion may occur even in the suburbs and the construction of full coverage ground network will incur huge costs. On the other hand, overcrowded base stations (BSs) will lead to increased competition and interference.

Fortunately, Space-Air-Ground Integrate Network (SAGIN) uses modern network technology to connect the space network, air network and ground network, which has inherent advantages of large coverage, high throughput and strong recovery ability, and can make up for the ground network in smart city.

As an important part of SAGIN, UAVs can play an important role in smart city [4], such as flight BSs, mobile relay stations, mobile caches and edge computing nodes. While deploying massive UAVs in smart city, some characteristics of UAVs should be considered. The coordination strategy between UAVs and other networks need be carefully made, including resource allocation, traffic offloading and mutual interference. Although energy storage technology has made great progress, limited available energy still restricts the wide application of UAVs and energy-aware optimization is still crucial. With scale increasing, the cost of deploying and maintaining UAVs could not be ignored.

SSAG is the application of SDN in SAGIN, which has better flexibility and extensibility [3] and is more conducive to centralized control. From the perspective of UAVs application in smart city, the problems of UAV control are reviewed and the new opportunities and challenges of UAV control based on SSAG architecture are discussed.

In this paper, section II introduces the SSAG framework. Sections III, IV, V discuss the application of UAV in smart city and the problems faced by the current application of UAV. Section VI describes the UAV control based on SSAG. In section VII, the advantages of UAV control based on SSAG framework are proved by a simulation example. The last section is the summary of the paper.

II. SSAG ARCHITECTURE

SDN aims to give network flexibility and agility. Through SDN controller, network management can be centralized logically. As the application of SDN in SAGIN, SSAG

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consists of three layers: infrastructure layer, control layer and application layer.

Infrastructure layer: includes all wireless communication nodes in the space network, air network and ground network.

Control layer: use two-layer control structure. The lower-tier SDN controller is responsible for controlling the underlying physical resources, such as satellite beam steering, UAV motion control, resource allocation. The upper-tier SDN controller is responsible for coordinating the operation of different networks.

Application layer: based on the control layer to achieve a higher level of network management, such as mobile management, data classification, and network supervision.

III. UAV Application Scenarios in Smart City

UAVs can play an irreplaceable role in smart city. Figure 1 shows several typical application scenarios of UAVs.

- UAVs as flight BSs: UAVs as flight BSs can establish a connection between satellite network and users or provide network services for users when the ground network is overloaded or there is no wireless access infrastructure.
- UAVs as mobile relay stations: UAVs as mobile relay stations can establish connection between ground stations with limited backhaul or ground stations and satellite network to balance traffic load.
- UAVs as mobile caches: UAVs as mobile cache can track mobile nodes (such as smart cars) or use high mobility of UAVs to collect data of remote devices.
- UAVs as edge computing nodes: UAVs carry mobile data processing module to analyze and process the data in remote areas to decrease delay.

There are many types of UAVs available. In this paper, large and medium-sized UAVs with large load capacity and flight duration are considered.

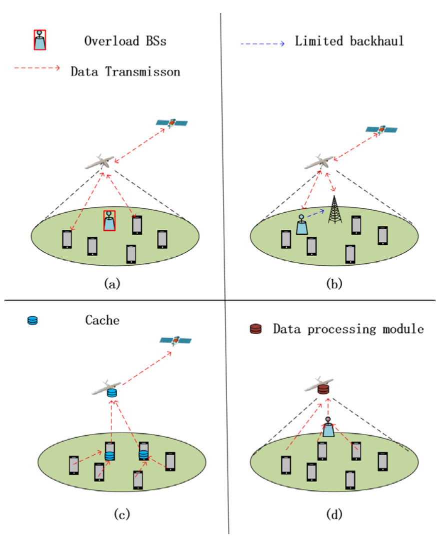

Figure 1. UAV support scenarios.
(a. UAVs as flight BSs; b. UAVs as mobile relay stations;
c. UAVs as mobile caches; d. UAVs as edge computing nodes)

IV. Research on UAV control

A. Main control objective

For UAVs: when UAVs provide users with wireless network services, the coverage and outage probability of UAVs are important performance indicators, reflecting the service quality of UAVs. Spectrum and energy efficiency reflect the utilization of resources from different angles and are important factors to evaluate the performance of UAVs.

For network system: bandwidth allocation aims to achieve specific network performance, such as minimum data loss, delay and power consumption. Increasing the bandwidth means consuming more power. Implementing bandwidth allocation strategy should balance power and information transmission. As satellites and UAVs in SSAG are moving and network topology is changing dynamically, it is a great challenge to ensure the reliability of message delivery. The transmission of high throughput with strict delay constraints is a continuous challenge of SSAG [6].

B. Main Control Considerations

UAV trajectory/configuration optimization: UAV trajectory/configuration optimization is mainly reflected in the control of UAV flight trajectory, flight altitude and UAV configuration. The energy consumption of UAVs is mainly generated by mechanical motion. The main purpose of flight trajectory optimization is to reduce the energy consumption of UAVs. The flight altitude of UAVs will affect the throughput of the system. Reference [7] studies the optimal altitude to generate the maximum throughput when UAV serves multiple ground nodes within its coverage. UAV configuration optimization will have a comprehensive impact on the system performance. Increasing the number of UAVs will increase the cost of UAV configuration and maintenance. While the number of UAVs also will affect system throughput. Due to the high mobility of UAVs, dynamic configuration of UAVs based on network states will be an effective solution.

Cross-layer collaborative: Cross-layer collaborative means that different networks in SSAG have unified control over resources, traffic load and mutual interference, mainly including bandwidth allocation, load balancing and cooperative transmission. Bandwidth allocation is designed to achieve specific network performance, such as minimum data loss, latency, and power consumption. There have been a large number of studies on bandwidth allocation for multi-networks collaboration [8-10]. The research of load balancing focuses on increasing system throughput and meeting the QoS requirements of different users. The research on network load balancing has been very mature in the ground heterogeneous network, but it cannot be simply transferred to SSAG and the dynamic of system and the characteristics of different networks should be fully considered. Collaborative transmission not only means to allow different networks to share wireless network resources dynamically, but also means to improve resource utilization and transmission capacity through planned control of users and networks in the system.

C. *Main control methods*

Centralized approaches: centralized approaches have a central controller to collect and process network states and make corresponding decisions. Network states usually include the states of users and networks in SSAG, including demand and type of users, movement direction and speed of UAVs and resource utilization of different network communication nodes. Through some optimization methods, although the centralized method can obtain the optimal strategy in theory, there are many problems in practice. Firstly, with the increase of network scale, the huge amount of network states will lead to the computational complexity to obtain the optimal strategy. Secondly, the channel resources and energy consumed will also increase with the increase of network scale. Thirdly, due to the high mobility of UAVs, it is difficult to realize the real-time control of UAVs in traditional network.

Decentralized approaches: decentralized approaches do not rely on the central controller to make decisions, and the UAV can make actions independently according to the surrounding network states. These approaches have the advantages of flexibility, invulnerability and low computation. However, decentralized approaches are difficult to apply to the case of cross-layer cooperation of multi networks. On the one hand, cross-layer cooperation needs to obtain global network states to make decisions, and it is difficult for UAVs to get enough information of other networks during flight. On the other hand, in the case of large-scale deployment of UAVs, A UAV needs to obtain the state information of other UAVs through link communication between UAVs and the links between UAVs need to be stable and reliable.

V. Analysis of UAV control problem

The control of UAVs needs to consider many factors. As mentioned above, the flight trajectory, flight altitude, transmission power and cooperation strategy with other networks of UAVs will have an impact on the performance of UAVs and the whole network system. Generally speaking, it is difficult to achieve every performance is optimal, different application scenarios will have different optimization objectives. However, regardless of the different algorithms and optimization objectives, the systematic difficulties of UAV control are basically the same. This is mainly due to the performance constraints of network system architecture and underlying physical layer devices.

Global information collection: the optimization goal of UAV control is not only for UAVs, but also for the performance of the whole network system. Due to the interaction between different networks in SSAG, the control of UAVs should not only consider the states of UAVs, but also other network states. Generally speaking, the more comprehensive the network system information, the better the UAVs and system performance. However, it is not a simple thing to obtain enough network states information in the multi network collaborative environment. We need to carefully design the collection, transmission and processing mechanism of the data between different networks in different scenarios. The current network system is difficult to meet the needs of global information collection, so many scholars have adopted some compromise approaches [11], but these approaches are obviously not the optimal solution.

Real-time control: the dynamic network states, the diversity of user needs and the mobility of UAVs lead to the rapid transformation of the network environment, which requires the UAVs to be able to change strategy in real time according to the current network environment. For centralized approach, the real-time control of UAVs is unrealistic. On the one hand, the continuous transmission of users and network states will occupy a large amount of channel resources. On the other hand, the real-time control of UAVs is a continuous time network optimization problem, which will lead to infinite accumulation of variables and high processing delay. For decentralized approaches, compared with centralized approach, each UAV needs to independently perceive the network states and make decisions, thus occupying less network resources and decreasing the computational complexity. However, due to the limited network states obtained by the distributed method, it is difficult for UAVs to obtain the optimal strategy. Game theory might be a good solution, but has not well studied

Multi-level information processing: The control of UAVs involves various considerations, which can be generally divided into two layers. First layer is system layer, controlling the configuration and flight trajectory of UAVs based on the whole system level. The purpose is to make full use of the flexibility and mobility of UAVs, dispatch UAVs for different regions according to the real-time information of the network states, and meet the network requirements in different regions at different time periods. Second layer is regional layer, which is based on the cooperation of different networks in the region to control the working mode of UAVs, including the flying height of UAVs, the signal transmitting power, the service users and the channel occupied. This layer is concerned with network performance within the region. In the case of a centralized approach, unified considerations for system-level and region-level UAV control become more complex and require huge computing resources as the scale increases. For the distributed method, it is difficult to control UAVs at the system level due to the lack of sufficient global states.

VI. Opportunities of UAV control in SSAG

Thanks to the layered structure and flexible deployment capability of SSAG, new possibilities are provided for UAV control. This paper builds a systematic UAV control scheme based on the SSAG network architecture. The detailed system configuration and function designs are described as follows.

A. *Multi-layer management architecture*

UAV control is implemented in a hierarchical manner. Specifically, in spatial dimension, the network is divided into different regions, which are controlled by hierarchical SDN controllers. The lower-tier SDN controller is responsible for the collaborative management of regional infrastructure (including UAVs), such as power control and user scheduling. Although the control of UAVs by the lower-tier SDN controller is centralized, it only needs to process the network information in the region, and does not need the intervention of the upper-tier SDN controller. The upper-tier SDN controller performs coarse-grained control, including UAV deployment, and can coordinate multiple lower-tier SDN controllers. Because part of the management functions are distributed to the lower-tier SDN controller, the upper-tier SDN controller does not need to receive all the network states information for decision-making, so the signaling overhead and the required computing resources are reduced.

In time dimension, network operations are performed in multiple time scales to deal with network dynamics. In large time scale, the upper-tier SDN controller adjusts the strategy according to the state of the upper-tier network (such as spatial traffic distribution or content popularity). In a very small time range, the lower-tier SDN controls update their strategies to meet the real-time demands of users. At different time scales, the corresponding SDN controller dynamically optimizes its control strategy according to the abstract network information. It should be pointed out that the information provided to all levels of SDN controllers for decision-making is different in space and time scales. For example, the upper-tier SDN controller needs the density of users, and the lower-tier SDN controller needs the detailed location information of users.

B. Near-real-time online learning architecture

The decision of SDN controller depends on the collection and analysis of information. Considering the scale and capacity of information, big data techniques can be adopted [12]. Through big data analysis, data features can be extracted to guide the decision of SDN controller. Because of the dynamic state of the network, the controller needs to constantly update the control strategy for the UAV. The real-time control of UAVs is not realistic. It is a good compromise solution to the near real-time control of UAVs based on a certain time interval. Therefore, a near real-time online learning framework is proposed for the upper-tier controller to control UAVs.

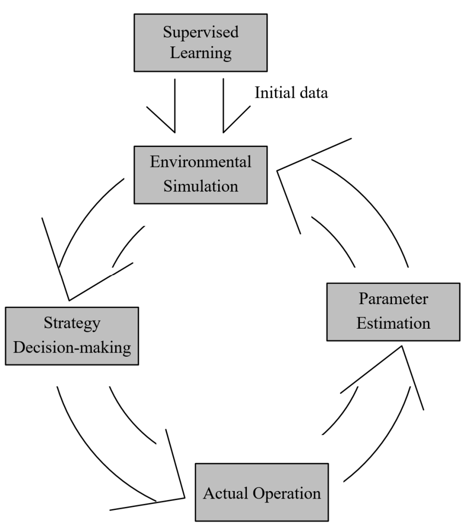

Figure 2. Online learning architecture

As shown in Figure 2, the online learning architecture is divided into four components: environmental simulation, parameter estimation, strategy decision-making and actual operation. Suppose that a time interval is used as the time interval of SDN controller for UAV control. Firstly, the state information of the network system in the last time interval is collected. The state information is collected in discrete time, and the network states chain of the last time interval is obtained. According to the obtained network states, feature quantity is extracted and feature parameters are updated by reinforcement learning algorithm. The initial feature quantity and feature parameters are obtained by supervised learning from empirical data. The characteristic parameters of different characteristic quantities represent the trend of network states transition. According to the characteristic quantity and characteristic parameter, the transition of network states in the next time interval is simulated, and the simulation results are used to formulate the control strategy of UAVs in the next time interval. According to the control strategy, UAVs perform network service tasks. Based on the above framework, loop in practice. Reference [13] shows that with the increase of loops, the performance of SDN controller for UAV control tends to the optimal value, and the approach has low computational complexity.

VII. CASESTUDY

Consider a smart city scenario. As shown in Figure 3, the city is simply divided into 9×9 regions, each of area is 200m×200m. The marked areas are residential areas and working areas respectively, the dotted line represents the route, and the upper left area is area a. Each area has a lower-tier SDN controller, and the intra-city network is managed by an upper- tier SDN controller. Simulation of traffic distribution in different areas at different times. The UAV has nine possible actions at any given moment, either hovering or flying into an adjacent area in eight directions. It is assumed that the lower-tier SDN controller in area can calculate the required number of UAVs. Figure. 4 shows the comparison of the number of UAV requirement in area a at every moment in a day and the UAV requirement in area a predicted by Near-Real-Time Online Learning Architecture at an interval of T=15min. According to the number of UAVs required by each area at each time, combined with the position and state of UAVs, the action trajectory of the UAV in the next time interval can be obtained through the strategy iteration algorithm in the simulation environment. Figure. 5 shows the comparison of throughput at every moment of a day through area a of near-real-time online learning architecture and the traditional method of allocating 2 UAVs on average for each area. It is obvious that the area a throughput obtained through near-real-time online learning architecture is superior to the traditional method.

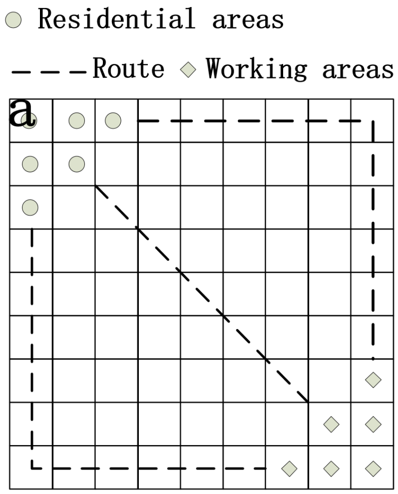

Figure 3. Scenario model

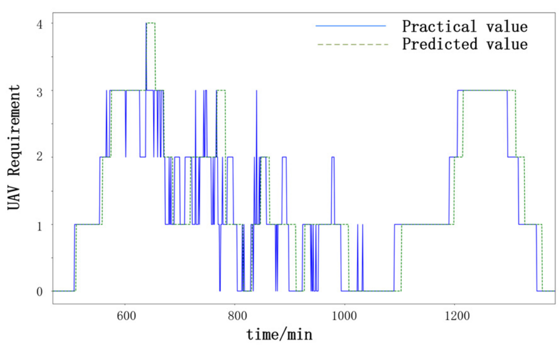

Figure 4. UAV requirements comparison

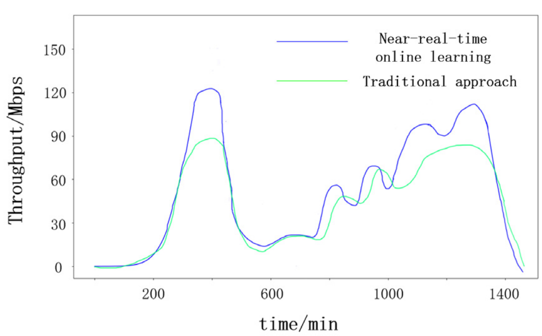

Figure 5. Throughput comparison

VIII. CONCLUSION

In this paper, the application of UAVs in smart city and the control of UAVs in SSAG framework are discussed in detail. Highlights the problems facing UAV control and possible solutions based on SSAG. A simulation example is to prove that the near-real-time online learning framework based on SSAG architecture is superior to traditional approaches in UAV control. However, the SSAG framework requires a large-scale replacement of the existing communication systems, which is difficult and expensive to construct and requires sufficient demonstration and careful design. At the same time, the application of new technologies such as network functions virtualization (NFV), mobile edge computing (MEC) and D2D will bring more beneficial possibilities for UAV control.

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